Artificial Neural Network Based Prediction of Energy Generation from Thermoelectric Generator with Environmental Parameters

Zi Yang Adrian Ang, Wai Lok Woo, and Ehsan Mesbahi

***Abstract*—This paper focus on a new methodology approach to evaluate more accurately the energy generated from Thermoelectric Generator (*TEG*) under the influence of its operating environmental parameters. An artificial neural network (*ANN*) model for predicting the energy generated by a *TEG* in its operating environment has been developed. The dataset generated through a validated finite volume method is trained in a supervised way and tested by a multi-layer perceptron (MLP) to predict the energy generated. However, the degree of ambiguity may vary widely across the whole range of input values therefore in this paper, a new methodological approach will be incorporated to not only predict the average value but as well as evaluating the reliability of the output value with the use of a scheme which is made up of two coupled neural network. Apart from predicting the output values, this model can perform reverse *ANN* to predict the input value when provided with an output value.**

***Index Terms*—Artificial neural network, energy, heat transfer, thermoelectric.**

I. Introduction

Artificial neural network (*ANN*) has become a modelling tool frequently used in application and analyzing complex problems in different discipline that cannot be easily modeled mathematically. Particularly, the *ANN* usage has been used widely in engineering applications such as heat transfer analysis, performance prediction and dynamic prediction [1], [2]. They have also been applied in many fields as a function approximation tool including time series prediction, regression analysis, interpolation and extrapolation; as a classification tool that include fault detection, pattern recognition and lastly as a data processing tool which include filtering and clustering [3].

ANN is known to be an adaptive system where all parameters are changed and deployed for solving problem. The changing of the parameter values is known as the training phase and the neural network is developed step by step with the optimization of criterion called the learning rule. Data, input and output, is a fundamental part of an *ANN* where the input data consist of a vector which can contain some image or raw data which is to be stored in the form of a vector. Upon feeding the inputs into the *ANN*, an error value is calculated using the difference between the actual and desired output. Depending on the architecture of the network, this error value will be fed back again into the *ANN* for adjustment of the parameters on the basis of the learning rule chosen. This looping will be done until the predicted output values become equal to the actual output or when an acceptable error value dictated by the user is achieved.

ANN has also been successfully used in the analysis of heat transfer data as well as heat transfer coefficient [4]-[6]. Sablani [7] in his research, developed a non-iterative procedure of an *ANN* to determine the fluid to particle heat transfer coefficient, Islamoglu [8] applied a new approach of an *ANN* model for predicting the rate of heat transfer of a heat exchanger which is the wire-on-tube type.

The advantages of using *ANN* from other methods is its capability in modeling a complex problems having many variables [9], handling of noisy data and can be implemented to any application [10]. Once a network is trained, parameters are fixed and any case can be executed within a short period without the need for re-programming and re-modeling [3].

In this research, a multilayer feedforward *ANN* model has been developed. This is the most common model used for mechanical engineering applications and that is being trained using propagation, genetic algorithm or simulated annealing technique. It consists of an input and output layer with at least one layer of processing units called the hidden layer between them [11], [12]. To improve on the reliability of the output value evaluated by the *ANN*, a two coupled neural network scheme is adopted.

II. Experimental Setup and Procedure

A. Experimental Model

A schematic diagram of the experimental apparatus used for the energy generation by the *TEG* is presented in Fig. 1. The conventional way of estimating the output voltage generated by a *TEG* is based on the surface temperature measured on the two ceramic substrates that sandwich the thermocouple. The output voltage generated will be dictated by the temperature gradient across the *TEG* as referenced to the voltage-temperature graphs stated in the manufacturer's technical sheet provided.

These set of values reported on the technical sheet in the form of a graph are usually obtained in a laboratory environment with little or no interference from the surrounding environmental parameters that the *TEG* is operating in, hence it will usually provide user with an output voltage generate by the *TEG* that has a huge variation from its actual output voltage generated.

Manuscript received September 5, 2016; revised February 5, 2017. This work was supported in part by Newcastle University, United Kingdom, and Temasek Polytechnic, Singapore.

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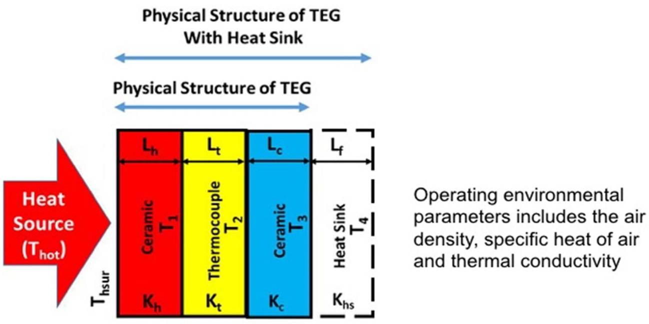

Fig. 1. Schematic diagram of experimental setup.

B. Experimental Procedure

In this model, a finite volume method for solving the three-dimensional heat transfer equation will be used. This will allow users to better predict and understand the distribution of the surface temperature on both the *TEG* ceramic substrates, taking into account the properties of air such as kinematic viscosity, specific heat, thermal conductivity and Prandtl number, as well as, those of the *TEG* material.

The *TEG* used in this research will be segregated into various regions as is shown in Fig. 1 where the thickness of the layers, thermal conductivity of the material used and areas are defined by *L*, *K* and *A* respectively.

The thermal conductivity of the substrates that sandwich the thermocouple will be taken into consideration, and also that of the thermocouple, while cooling of the *TEG* will be attributed to air velocity at cold side of the *TEG*. Therefore, temperature gradients measured across the thermocouple in this manner can relate to a more realistic output voltage.

To increase the temperature gradient across the *TEG*, metal heat sink can be attached onto the *TEG* surface on the cold side to help with the dissipation of heat from the hot side ceramic substrate hence achieving a higher temperature gradient. This increment in the temperature gradient across the *TEG* will be translated proportionally to an increase in the output voltage base on the graphs provided in the manufacturer specification sheet. Parameters that determine the output voltage in this scenario with the heat sink attached are, in addition to those mentioned previously, the thermal conductivity of the heat sink, its geometrical arrangement, as well as, the air flow characteristics across the metal heat sink used.

C. Model Validation

A mathematical model that incorporated the various heat transfer coefficients at different area of the *TEG* and the effects of the environmental parameters is being formulated.

The validation of the mathematical model is carried out using a *TEG*1-1263-4.3 from Thermal Electronics Corp, a 11-volt light emitting diode acting as the heat source and a metal heat sink of the same size as the footprint of the *TEG* used.

The experimental setup is done in an air conditioned environment with a constant ambient temperature of 21^{o}C and wind velocity of approximately 0.1m/s. The heat sink of the 11-volt light emitting diode is used as the heat source, generating approximately 30^{o}C to 40^{o}C of thermal heat onto the hot side substrate surface of the *TEG*.

Temperature gradient across the thermocouple is measured and logged by a type T thermocouple sensor on both the hot and cold side substrate. Ambient air temperature is also logged to ensure that the ambient temperature remain constant as shown in Fig. 2 and the schematic overview as shown in Fig. 3.

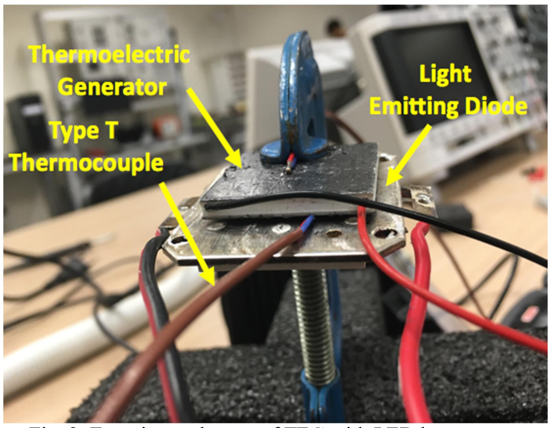

Fig. 2. Experimental setup of TEG with LED heat source.

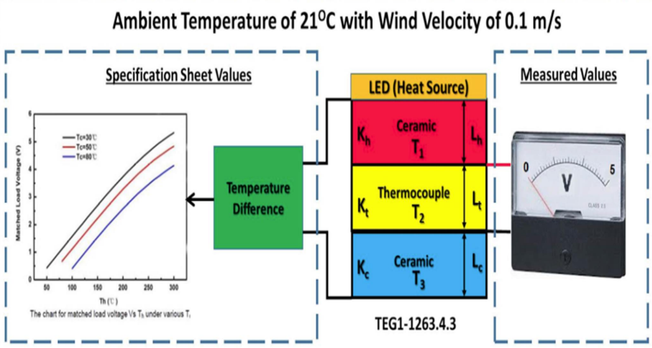

Fig. 3. Experiment setup schematic overview.

Using the temperature gradient obtained, a comparison was done between the output voltage, reference from the specification sheet graph, the output voltage measured by a digital voltmeter and finally the output voltage calculated by the mathematical model.

This experiment serves to validate the results obtained from the actual setup shown in Fig. 2 with both output voltages obtained from the specification sheet graph and the mathematical model. The results show that the values obtained from the specification sheet provided by the manufacturer varies from the actual measured output voltage whereas the values calculated by them mathematical model is almost the same with little variations. Hence we concluded that the mathematical model which takes into consideration the environmental parameters is able to produce reliable and precise results for future *TEG* output power analysis with an error rate of approximately $\pm$0.15%.

Therefore, using the verified mathematical model discussed above [13], a set of input data pattern and corresponding targets will be generated for the use of training and testing by the neural network model.

III. Artificial Neural Network

A. Artificial Neural Network Architecture

The *ANN* model used in this research is a multilayer, feed forward, back propagation error neural network for heat segmentation to distinguish the various output voltages generated by the *TEG*, with and without the aid of a heat sink. It has three layers, namely the input, hidden and output [14].

There are a total of 12 input variables that addresses the operating environmental parameters and material construction of the *TEG*. The 12 input variables are, ambient temperature on both hot and cold side, thickness of ceramic substrates, wind velocity on both hot and cold side, thermal conductivity of material on both hot and cold side, length of the thermocouple sandwiched between the two ceramic substrates, thermal conductivity of the thermocouple material, length of the heat sink fins, area of the *TEG* surface as well as the surface temperature of the *TEG*. The three output variables used in this system are output voltage generated with reference from the manufacturer's specification sheet; output voltage generated using the mathematical model with the *TEG*'s operating environmental parameters and lastly output voltage generated using the mathematical model with operating environmental parameters and with a metal heat sink to help with the dissipation of heat from the cold side ceramic substrate.

The training of this system is performed in a supervised way by using 50% of the dataset generated as training data and the remaining 50% as validation data. First output scenario will be trained using 11 inputs leaving out the tenth input, which is the length of the metal heat sink fin, and second output scenario will be trained using 11 inputs and similarly leaving the tenth input out and lastly for the last output scenario, all 12 inputs will be used for the training.

The changes in heat intensity on the *TEG* influenced by the environmental parameters will lead to different output voltage generated by the *TEG*. All the data generated from the finite volume analysis as well as environmental factors defined by users are consequently combined to produce one large dataset for neural networks fusion. This new dataset consists of 4096 sets of parameters.

The number of hidden layer nodes in each network is determined by applying the formula as shown in equation 1.

$$n_h = \left(\frac{n_i + n_o}{2}\right) + \sqrt{(n_p)} \qquad (1)$$

where n_h, n_i and n_o are the number of hidden, input and output layer nodes respectively and n_p is the number of training samples in the dataset used therefore the number of hidden layer nodes used for each neural network is 70 nodes (n_i=12, n_o=3 and n_p=4096).

There will also be various training functions available for training the *ANN*. They are the Levenberg-Marquardt back propagation, Bayesian regularization back propagation, Scaled conjugate gradient back propagation and lastly the Resilient back propagation. In this research, the Levenberg-Marquardt back propagation method will be used as it is known to be much more efficient than either of the other techniques when the network contains no more than a few hundred weights. The Levenberg-Marquardt algorithm is as shown in equation 2,

$$x_{h+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (2)$$

where *J* is a Jacobi matric that contains first derivatives of the network errors with respect to the weights and biases, *e* is the vector of network errors, μ is a momentum parameter,

B. Coupled Neural Networks

Uncertainties may arise due to inaccuracy in the measurement of the inputs and outputs or that the values measured do not provide a complete specification of the behavior of the system.

It has been proven that neural network is able to learn deterministic relations or to extract the characteristic parameters of stochastic process and has a computational power that is as wide as a large class of symbolic languages. In the context of constructing a model for physical phenomena by neural networks, the issue with learning from data with error bars has been discussed in various research work [15]-[18].

In this research we are mainly concern over the ambiguous data rather than smoothing out the data which is not representative of the actual setup. The ambiguity situation is rather complex as the uncertainty is not uniform throughout the parameter space. There will be cases where the regions of parameter spaces provide an ambiguous answer and other where they are not sufficient to provide an accurate answer. Therefore, it will be useful to develop a coupled neural network that will provide the most probable outcome and at the same time, able to identify how reliable the result is.

The coupled neural network shown in Fig. 4 shows a system that comprises two coupled network where one learns in a supervised way and the other provide the expected error of the result for that particular input. Both networks have the same architecture and are trained using the same dataset. In order to avoid any large fluctuation of results, the second network will only start learning after the first has stabilized and finish training.

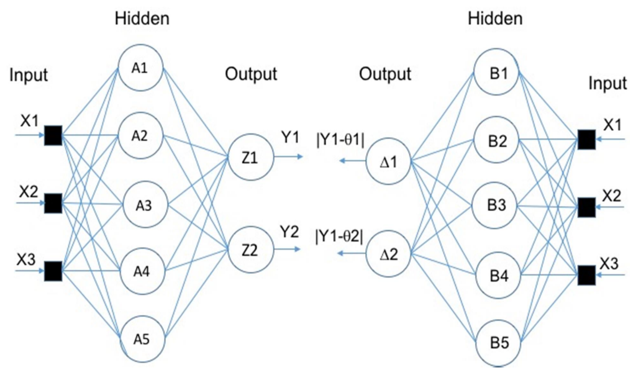

Fig. 4. Coupled Network.

where the first network architecture on the left can be approximated by,

$$fw(\vec{x}, t+1) = \\ fw(\vec{x}, t) - 2\eta \frac{\partial f}{\partial W}\left(fw(\overrightarrow{x}) - \bar{y}(\overrightarrow{x})\right)\frac{\partial fw}{\partial W} \qquad (3)$$

where $\bar{y}(\overrightarrow{x})$ denotes the average value of the random variable y at the argument $\vec{x}$.

Similarly for the second network architecture, with the output $gw'(\overrightarrow{x})$ and the same input $\vec{x}$ is constructed according to the learning law.

$$gw(\vec{x}, t+1) = gw'(\vec{x}, t) + \frac{\partial gw'}{\partial W'} \Delta W' \quad (4)$$

With error function

$$e' = (gw'(\vec{x}) - (fw(\vec{x}) - y(\vec{x}))^2)^2 \quad (5)$$

with

$$\Delta W' == -\eta' \frac{\partial e\prime}{\partial w\prime} \quad (6)$$

The main idea of this system is not to smooth out fluctuations in the data to obtain an approximate output but instead it is used to characterize the ambiguity for each region of input space.

C. Reverse Artificial Neural Network

Part from being able to predict the output voltages of different scenarios, the *ANN* is also able to predict the selected input value when given an output voltage required for a specific application.

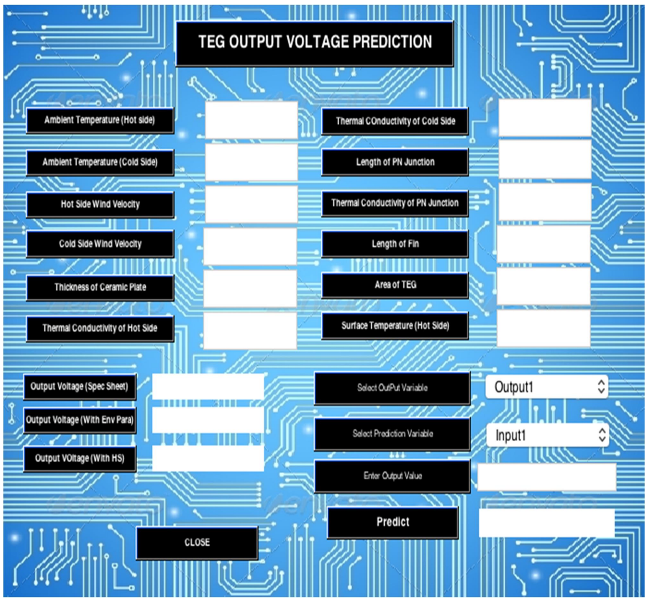

Fig. 5. Graphical user interface for *ANN* architecture.

User will first determine the output voltage for a particular scenario that is required by the *ANN* model to predict the input parameter. The system will first train itself for this scenario and predicts the value of the input variable by using remaining inputs and one output variable as training data to predict that specific input variable.

This function will enhance the versatility of the *ANN* model by not only allowing the predicting of output voltage but vice versa, predicting the input variable required hence allowing users to modify the environmental parameters to achieve the required output voltage.

D. Graphical User Interface

Interactive graphical user interface (GUI) as shown in Fig. 5 will be used to fulfil the functionality of the *ANN* model.

GUI will guide and allow users to train the set of input data using their preferred training function and after which, an interface that allow users to input the 12 variables in order to let the *ANN* model predict the three output voltages for the various scenarios.

IV. Results

Training of the *ANN* model is done using 50% of the dataset as training data and the remaining 50% as validation data. Each individual output voltage scenarios will be trained individually.

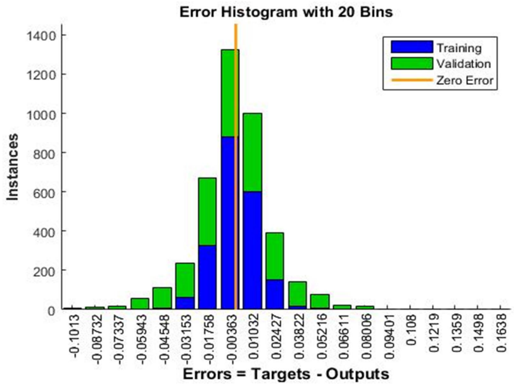

Fig. 6. Error histogram.

The error histogram shown in Fig. 6 indicated that most of the errors fall between -0.06 and 0.06 with no obvious outliners outside of this range for network three.

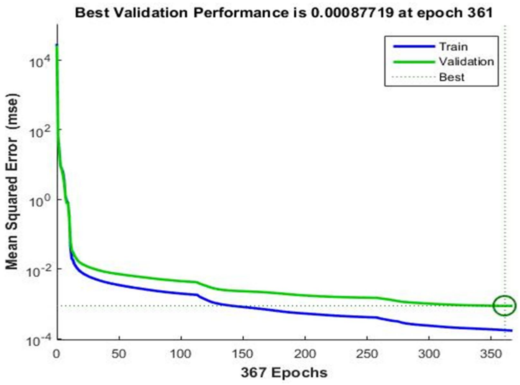

Fig. 7. Validation performance graph for network three.

Fig. 7 shows the mean squared error (MSE) for network three. Validation errors are used to stop training early if the network performance on the validation vectors fails to improve or remain the same, as indicated by an increase in the MSE of the validation samples.

The best validation performance for network three is 0.00087719 at epoch 361 and the plots did not indicate any major problems with the training.

Fig. 8 shows the regression plot for training, validation and the entire dataset. The dashed line in each axis represents the perfect results. The solid line represents the best fit linear regression line between the output and targets. In these plots, all our R=1, meaning that there is an exact linear relation between output and targets.

From the plots, it indicates that the system is giving very low MSE values and therefore it is behaving very well and generating good results for the training.

Fig. 9 shows the output voltage generated by the ANN model using the same set of environmental and construction parameters that influence the operation of the experimental setup shown in Fig. 2 and comparing it against the values obtained from the manufacturer's specification sheet as well as actual measured values.

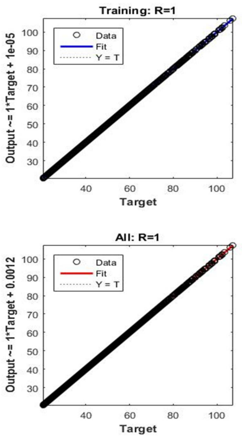

Fig. 8. Regression graph plot for network 3.

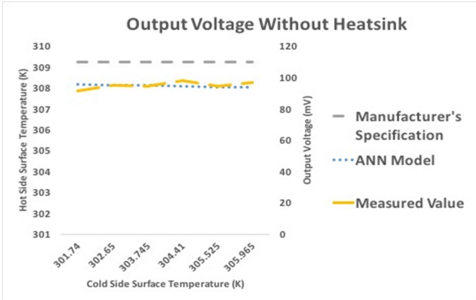

Fig. 9. Results from validating ANN model.

The results indicated that the output voltage generated by the ANN model has a mere difference of approximately 0.3% when compared to the actual measured output voltage whereas the output voltage obtained from the manufacturer's specification sheet has a difference of approximately 14% when compared to the actual measured voltage. This could be due to the fact that the environmental parameters that the TEG is operating in plays a significant role in the generation of energy by the TEG. Therefore, the ANN model provide users with a more precise estimation of the output voltage as compared to values obtained from the manufacturer's specification sheet which the data are usually obtained in a laboratory based environment often excluding the effects of operating environmental parameters.

V. Conclusion

To conclude, an ANN model is being developed for the predicting of output voltages generated by the *TEG* taking into consideration of its operating environmental and *TEG* construction parameters. This computational scheme is able to predict both the input parameters and output voltage values as well as the ability to evaluate the predictive model with a degree of reliability, although not perfect but improves the reliability checks of the predicted output voltage generated by the *TEG* hence allowing users to choose the *TEG* suitable for their applications thereby improving on efficiency.

Therefore, the *ANN* model is a reliable and flexible mathematical structure for the modeling and prediction of results due to its accuracy and therefore, can be used to simulate the experiments precisely.

Acknowledgment

Zi Yang Adrian Ang would like to thank those who has provided good advices and constructive ideas on the development of the computational scheme model.

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